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Fault Detection and Classification in Underwater Vehicles Using the T^2 Statistic

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Preliminary communication

Failure detection and classification are crucial steps in the implementation of reconfigurable control. This paper describes the application of the Hotelling T^2 statistic to the detection and classification of stern plane and rudder jams in underwater vehicles. Simulation results with and without measurement noise are presented. Results indicate that this method is capable of providing rapid and reliable detection and classification of these faults.

Key words: failure detection, failure classification, reconfigurable control

1 INTRODUCTION

This paper deals with fault detection and classification as a part of our on-going research in the integrated design of reconfigurable control systems. The objective of reconfigurable control is to provide fault-tolerant control in an uncertain or changing environment. This will be accomplished by detecting changes in the current operation of the system from what is expected and then changing the controller model so that acceptable performance is achieved. The approach that we are investigating is the use of a data-driven method with the Hotelling T^2 statistic [1, 2, 3] for fault detection coupled with the use of multiple controllers, each designed for a different operating condition. These different conditions may include failure modes as well as less severe changes in the environment that cause significant differences in the system's behavior.

The aim of the controller design procedure is that, as far as possible, each of the controllers that are designed for the various models should simultaneously stabilize all the models. This will prevent loss of control during the time it takes to detect the change in the system.

There are two major approaches in monitoring a process for detecting faults and classifying them. One is model-based, and the other is model-free. The data-driven method is related to the latter. The former is related to analytical redundancy [4]. Most developments using analytical redundancy are based on forming a residual process that requires statistical testing and decision making for the detection. Among the developments are Gertler and Singer [5], Frank [6], and Isermann [7]. Gertler and Singer achieved analytical redundancy by constructing a set of parity equations out of all the possible input-output relationships of the explicit plant model. While their methods are developed for open-loop systems, Frank [6] and Isermann [7] investigated closed-loop systems by using observer-based methods and parameter estimation, respectively.

Most analytical redundancy measures require fairly accurate models in order to be effective. Since accurate models are typically difficult to obtain, many process-monitoring methods in industrial processes are based on data-driven measures, although this approach is largely dependent on the quantity and quality of the process data.

In this paper, the fault detection and classification steps are performed using the T^2 statistic and Principal Component Analysis (PCA). The statistic is computed based on the comparison of a set of measured variables over a block of time with basis data for those variables that show the expected behavior of the system. This approach asserts its effectiveness to cure the short falls in the simple model-free methods by taking care of both spatial and serial correlation problems in the observation variables.

Section II describes the T^2 statistics and principal component analysis as we are applying it in this research. Simulation results with and without measurement noise are presented in Section III and conclusions are presented in Section IV.

2 FAULT DETECTION AND CLASSIFICATION

A. Overview

The first step in reconfigurable control is to detect the need to change the controller. There must be some form of system identification or fault detection that is performed. The approach that is used here is fault detection and classification rather than an explicit identification of the system model. In the context of this research, a fault refers to any change in the system dynamics that would significantly affect the performance of the system in response to reference commands. Thus, a fault does not necessarily refer to a catastrophic failure to the system or the loss of a major component. A fault may be the result of parameter changes in the system model due to changes in the operating environment. However, our work to date has focused on stern plane and rudder jams only. In previous work on surface ships [3], use of the T^2 statistic was also able to rapidly detect more subtle changes in the system model.

The approach used for the T^2 statistic is to compare a set of measured variables collected during the current operation of the system with training (basis) data for the same variables that represent the desired or expected behavior of the system [1]. The basis data can be generated on-line if an accurate model is available that is sufficiently fast to meet the computational demands of real-time performance. Otherwise, the basis data would need to be precomputed and stored.

If the value of the statistics is less than a specified threshold, then the decision is made that the actual system is operating sufficiently close to its desired behavior, and no change in the controller is required. If the threshold is exceeded by the T^2 statistics, then the decision is made that there are changes in the actual system relative to the basis system, and the controller should be reconfigured. If this is the case, then the next step is to classify the fault to decide what controller should be used.

B. Processing the Basis Data

Generation of the basis data involves collecting full-scale data from the system during specified maneuvers or by running simulations of the system using an accurate model. If the basis data can be generated on-line using the same reference commands as the actual system, then there is no need to store large amounts of data representing different operating scenarios. This is definitely the preferred approach. The recursive neural network (RNN) model of submarine dynamics developed by our sponsor is ideal for this purpose since it is able to generate accurate solutions to the equations of motion at speeds much faster than real time. Both the RNN model and SIMULINK models have been used in this work.

Data are processed over blocks of time. Several physical variables are measured and stored at consecutive sample times for a specified interval of time. The number of variables that are measured is denoted by n_{meas}, and the number of measurements that are taken in each block of time is denoted by n_{obsv}. The basis data within the block are stored in matrix $\boldsymbol{A}$, which has n_{obsv} rows and n_{meas} columns, with $n_{\text{obsv}} > n_{\text{meas}}$, so that

$$\boldsymbol{A} = \left[b_1 \ \vdots \ b_2 \ \vdots \ \cdots \ \vdots \ b_{n_{\text{meas}}} \right] \tag{1}$$

where each b_i is a physical variable sampled at n_{obsv} consecutive time points. The processing described below is performed for each block of data as it is collected.

After the matrix $\boldsymbol{A}$ is formed for the current block of data, it is auto-scaled by the means and standard deviations of the physical variables. The means and standard deviations of each of the physical variables (columns of $\boldsymbol{A}$) are computed over the n_{obsv} points in time. The variables are scaled by subtracting the means from the measured values and dividing the results by the standard deviations.

Once the scaling of the data is completed, Principal Component Analysis is then performed on the scaled variables. This step determines the eigenvectors of the covariance matrix of the basis data and allows for reduction in the dimensionality of the data to include only those directions in the vector space that are most significant for showing variations in the training data [8]. The singular values and eigenvectors are computed using singular value decomposition of the data based on the relationship

$$\boldsymbol{U\Sigma V}^T = \frac{\boldsymbol{A}}{\sqrt{n_{\text{obsv}} - 1}} \tag{2}$$

where the diagonal elements of the matrix $\boldsymbol{\Sigma}$ are the singular values, and the columns v_i of the matrix $\boldsymbol{V}$ are the orthonormal eigenvectors of the covariance matrix of the basis data. The relative magnitudes of the singular values are compared, and only the n_{var} largest singular values and the corresponding eigenvectors are retained. This reduction in dimensionality of the data is particularly important when using the T^2 statistic since the smaller singular values effectively act as noise sources when computing the statistics and thus impair its reliability [1, 9]. The reduced dimensionality also reduces the computational burden in the remainder of the data processing.

Once the value of n_{var} has been determined, the n_{var} largest singular values are used to form the diagonal matrix $\boldsymbol{\Sigma}_{n_{\text{var}}}$, and matrix $\boldsymbol{P}$ is formed from the first n_{var} columns of $\boldsymbol{V}$. Thus, $\boldsymbol{\Sigma}_{n_{\text{var}}}$ is a square matrix with n_{var} rows and columns and $\boldsymbol{P}$ has n_{obsv} rows and n_{var} columns.

$$\begin{aligned} \Sigma_{n_{\text{var}}} &= diag\left[\sigma_1 \,\vdots\, \sigma_2 \,\vdots\, \cdots \,\vdots\, \sigma_{n_{\text{var}}}\right] \\ P &= \left[v_1 \,\vdots\, v_2 \,\vdots\, \cdots \,\vdots\, v_{n_{\text{var}}}\right]. \end{aligned} \tag{3}$$

C. Determining the Number of Significant Variables

The fault detection task using the T^2 statistic projects the measured data collected during system operation into a vector space defined by the eigenvectors obtained from the training data. When singular value decomposition (SVD) of $\boldsymbol{A}$ is performed, there are n_{meas} eigenvectors and singular values. In general, there will be a large dynamic range to the singular values. In order for the T^2 statistic to be used reliably, the smaller singular values and the corresponding eigenvectors must be discarded. The smaller singular values act as noise sources in the calculation of the statistic, reducing its reliability. Only those directions in vector space that describe the major variations in the training data should be used during fault detection. Those directions correspond to the n_{var} largest singular values.

One method for determining the appropriate value for n_{var} is to compare the singular values of the $\boldsymbol{A}$ matrix with the singular values of a noise matrix of the same dimensions as $\boldsymbol{A}$. This is known as the Parallel Analysis Method [1, 10]. A matrix $\boldsymbol{B}$ of independent random numbers is generated and then auto-scaled by its mean and standard deviation in the same fashion as for the $\boldsymbol{A}$ matrix. Singular value decomposition is done for $\boldsymbol{B}$, and those singular values are compared with the ones for $\boldsymbol{A}$. The number of significant variables that are retained, n_{var}, is equal to the number of singular values of $\boldsymbol{A}$ that are larger than the corresponding singular values of $\boldsymbol{B}$. Therefore, any singular values in the basis data that are smaller than the singular values of »pure« noise are discarded. For the basis data collected in various simulations, only one singular value of $\boldsymbol{A}$ exceeded the noise values for most every combination of measured variables and blocks of time. In a few cases, there were two such singular values.

D. Processing the New Data

During actual operation of the system, measurements are made of the same physical variables and over the same intervals of time, as was done for the basis data. The new data in each block are stored in a matrix with n_{obsv} rows and n_{meas} columns. The data are then auto-scaled using the means and standard deviations computed from the basis data.

The value of the T^2 statistic is then computed for each of the rows of the new data matrix, using the $\boldsymbol{P}$ and $\boldsymbol{\Sigma}_{n_{\text{var}}}$ matrices defined in (3). Letting x_i^T represent the $1 \times n_{\text{meas}}$ vector that is the i^{th} row of the matrix containing the scaled new data, the T^2 statistic for that vector of measured physical variables is [1]

$$T_i^2 = x_i^T P(\Sigma_{n_{\text{var}}}^2)^{-1} P^T x_i . \tag{4}$$

The T_i^2 statistic is the square of the scaled 2--norm of the $n_{\text{var}} \times 1$ array $z_i = P^T x_i$, with the scaling being done by the inverses of the significant singular values (or eigenvalues) of the basis data. The elements of the array z_i are the coordinates of the orthogonal projection of the data vector x_i into the space defined by the significant eigenvectors from the basis data, expressed in terms of those eigenvectors.

If the actual data vector x_i lies primarily in the space spanned by the n_{var} most significant basis eigenvectors, and if the values of the various elements of x_i are »reasonably close« to the corresponding values from the basis data, then it can be decided with reasonable confidence that the vector x_i belongs to the same class as the basis data. However, if the data x_i has a large component orthogonal to the space spanned by the n_{var} most significant basis eigenvectors and/or the elements of x_i are considerably different from the corresponding elements of the basis data, then it can be concluded that the new data vector does not belong to the same class as the basis data.

At the end of each block of time, the value of a »summary« statistic is compared with the T^2 threshold. Our experience has shown that fault detection is more reliable if a summary statistic representing the entire block of data is used rather than comparing each of the n_{obsv} values of the T_i^2 statistic with the threshold. Various operations on the n_{obsv} values of the T_i^2 statistic within each block were evaluated to see which would be most reliable. The »summary« statistic for each block that was chosen is the sum of the natural logarithms of the T_i^2 values within the block.

$$T_{Sum}^2 = \sum_{i=1}^{n_{\text{obsv}}} \ln\left[T_i^2\right]. \tag{5}$$

The threshold for this summary statistic was computed in a similar fashion from the T^2 threshold.

$$T_{Sum-\text{treshold}}^2 = n_{\text{obsv}} \cdot \ln\left[T_{\text{treshold}}^2\right] \tag{6}$$

with the $T^2_{\text{threshold}}$ given by [1]

$$T^2_{\text{treshold}} = \left[\frac{n_{\text{var}}(n_{\text{obsv}}-1)(n_{\text{obsv}}+1)}{n_{\text{obsv}}(n_{\text{obsv}}-n_{\text{var}})} \right] \times \\ \times F_{\alpha}(n_{\text{var}}, n_{\text{obsv}}-n_{\text{var}}) \qquad (7)$$

where $F_{\alpha}(n_{\text{var}}, n_{\text{obsv}}-n_{\text{var}})$ is the F distribution for the $100(1-\alpha)$ % confidence level with n_{var} and $n_{\text{obsv}}-n_{\text{var}}$ degrees of freedom [1, 2, 11]. Values of $\alpha=0.05$ and $\alpha=0.01$ have been used during this research.

E. Decision Making

Both fault detection and fault classification are performed by comparing the summary statistic T^2_{Sum} computed at the end of each block of data with the summary threshold from (6). The incoming basis data and new data are each split into two sets of measured variables. The variables that represent motion in the horizontal plane are grouped together, and the variables that represent motion in the vertical plane are grouped together. The PCA computations are performed individually on the two groups of basis data. The two groups of new data are also processed individually, and separate T^2_{Sum} statistic are computed and compared with their corresponding thresholds. If the same number of variables are retained in each group after the PCA computations, then the thresholds are equal, although in general they can have different values. In the results reported here, the same number of measurements and retained variables have been used in each group.

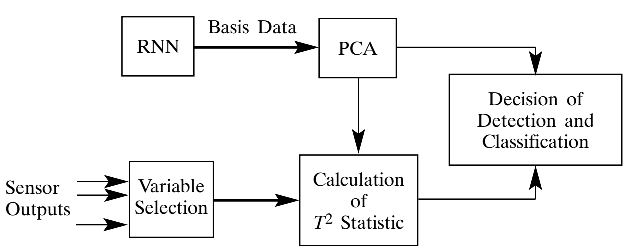

Fig. 1 Operations in failure detection and classification with the T^2 statistic

If one and only one of the T^2_{Sum} statistic exceeds its threshold, then the decision is made that a fault has occurred and the type of fault is stern plane jamming if the vertical-plane statistic exceeded its threshold or rudder jamming if the horizontal-plane statistic exceeded its threshold. If both of the statistics exceeded their thresholds, then the fault classification is based on the statistic with the larger value (assuming the thresholds are equal). Figure 1 illustrates the operations in the fault detection and classification with the T^2 statistic.

If more than two fault classes are to be considered, then the above approach can be extended by computing additional T^2 statistics and thresholds. Other methods, such as Fisher Discriminant Analysis (FDA) and Quantification of Contributing Variables (QCV), can also be used. These methods are currently under investigation.

3 SIMULATION EXPERIMENTS AND RESULTS

The fault detection and classification capabilities of the T^2 statistic have been tested in numerous computer simulations involving stern plane jams and rudder jams in a nonlinear submarine model. A description of the simulation setup is presented below. That is followed by a description of our results in detection and classification of faults when there is no measurement noise. Finally, our preliminary results in the presence of measurement noise are presented.

A. Description of the Simulation

The simulations were performed in SIMULINK using the nonlinear equations of motion for the submarine model. The only exception to full six degree-of-freedom motion was that the total velocity $U=\sqrt{u^2+v^2+w^2}$ was held constant throughout a simulation. The sway and heave velocities were obtained during the solution to the differential equations at each simulation timestep, and the surge velocity was computed from the constraint on U. Most simulations were performed at 12 knots. The simulation timestep was 0.125 seconds in every case.

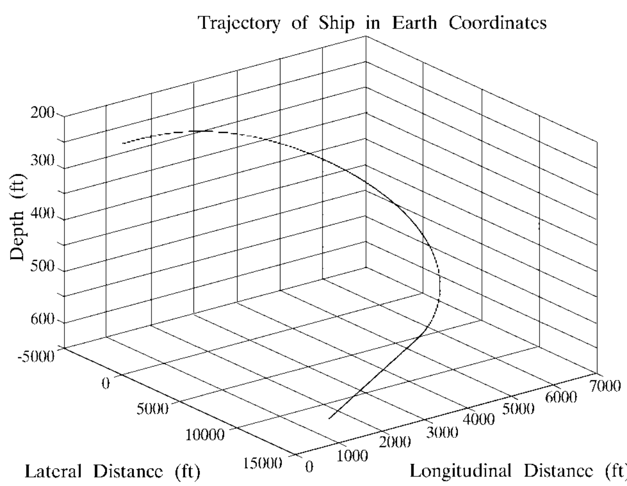

Fig. 2 x-y-z coordinates for basis simulation at 12 knots

The trajectory taken in each of the simulations was a combined course and depth change. Depth was changed from 200 feet to 600 feet at the same time that the course was changed by a starboard turn of 120 . Reference trajectories were generated for depth, pitch angle, and yaw angle. The submarine was assumed to be neutrally buoyant at the initial depth, and a cubic equation was used to compute the weight-buoyancy error as a function of depth. Figure 2 shows the submarine trajectory during a basis simulation.

The controller used in the simulations was an LQR design. The variables that were measured were {depth, pitch, depth rate, pitch rate} for the vertical plane motion and {roll, yaw, roll rate, yaw rate} for the horizontal plane motion. The measured values were generated by numerical solution of the nonlinear equations of motion at each simulation time step. Control variables were {rudder, stern plane, bow plane}. The control signals were generated based on the difference between the measured variables and the reference trajectory variables. The control signals were saturated at ± 35 , ± 20 , ± 25 for the rudder, stern plane, and bow plane, respectively. In simulations of a failure mode, either the stern plane or the rudder was jammed at a specified time during the simulation. The control surface was jammed at its current value at that time.

B. Simulation Results without Measurement Noise

Numerous simulations were performed during this research to develop our methods for failure detection and classification. The results that are presented in this paper summarize that work. The simulations were for a speed of 12 knots with either a stern plane jam or a rudder jam occurring at some point in the simulation. The fault detection/classification algorithm had no knowledge of the type of failure or the time at which the failure occurred.

The first set of results that will be discussed considers only stern plane jams. Although there is only one type of fault in this case, the detection/classification algorithm has no knowledge of that; it just processes the measured data. Therefore, missed detections and mis-classifications are still possible. Simulations involving only rudder jams will be discussed next.

B.1 Stern Plane Jams

In these simulations, the stern plane was jammed at its current value at a selected point in the simulation. The time of the fault was varied from 50 seconds to 600 seconds, in 0.25 increments. This results in 2, 201 simulations. For each simulation, the measured variables and the basis data were processed by the fault detection/classification algorithm utilizing the PCA computations and the T^2_{Sum} statistic. If a fault was detected, the time of detection was recorded along with the type of fault detected. If no fault was detected, a default detection time of 1 000 seconds (the end of the simulation) was recorded. The upper limit of 600 seconds was chosen for the faults because the stern plane and rudder are both in steady-state conditions beyond that time in normal operation. Since those control surfaces are not changing in the basis data in the latter stages of the simulation, it is difficult to detect a jammed condition. Some form of »persistent excitation« is needed to achieve rapid detection.

The parameters used in the fault detection/classification algorithm for these simulations were $n_{var}=2$, $n_{obsv}=17$, and $\alpha=0.05$ (95 % confidence interval). The measured variables for the vertical plane were depth and pitch, and for the horizontal plane they were roll and yaw.

Figure 3 shows the results from these simulations, with the length of time taken to detect the failure plotted versus the time at which the failure occurred. Each circle in the figure represents the outcome of one simulation. Except in the ranges 310–320 seconds and 460–470 seconds, most of the detections occur within 6 seconds of the failure. Each of those time intervals occur near the time the stern plane reverses direction, but the reason for the increase in detection time is not clear. Of the 2, 201 simulations, correct classification of the fault as a stern plane jam occurred in 2, 187 cases, a 99.3 % rate of successful classification. In each of the other 14 simulations, the fault was mis-classified as a rudder jam. There were no missed detections in this set of simulations. In the 2, 187 cases of correct classification, the mean time to detect the failure was 4.45 seconds, and the maximum time for detection was 14 seconds. In the 14 cases of incorrect classification, the mean and maximum times for detection were 8.30 seconds and 12.4 seconds, respectively.

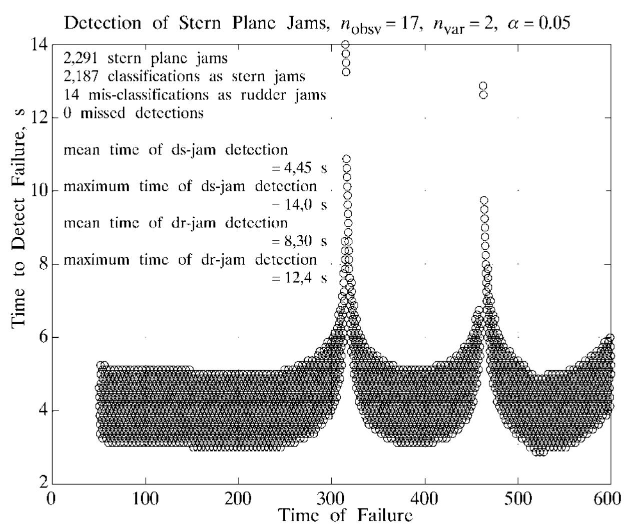

Fig. 3 Detection and classification of stern plane jams

In the 2, 201 simulations, the stern plane T^2_{Sum} statistic exceeded its threshold 2, 198 times. The stern plane threshold was not exceeded in 3 consecutive simulations, with the times of failure centered at 462 seconds. The rudder threshold was exceeded in those simulations, so these account for 3 of the 14 cases of mis-classification. The rudder T^2_{Sum} statistic exceeded its threshold 803 times. In 11 of these cases, the rudder T^2_{Sum} statistic was larger than the stern plane T^2_{Sum} statistic, accounting for the other 11 mis-classifications. In the remaining 792 simulations where both thresholds were exceeded, the stern plane T^2_{Sum} statistic was larger than the rudder T^2_{Sum} statistic, so the fault classification was correct. The times that the stern plane jammed in the 803 simulations where the rudder threshold was exceeded ranged from 88 to 508 seconds in a fairly uniform fashion.

The effects that the parameters in the fault detection/classification algorithm have on the detection time were studied for the case of the stern plane jam occurring at 250 seconds. It is felt that similar results would be obtained with other starting times for the fault. Figure 4 shows the results of this study. The number of significant variables (n_{var}) was given values of 1 and 2. The value of n_{var} is one of the parameters in the F distribution. The other parameter is the value of $n_{\mathrm{obsv}} - n_{\mathrm{var}}$, and this was given values of 10, 15, 20, 25, 30, 40, and 60. Therefore, the number of observations in a block of data varies with these two parameters. Confidence intervals of 95 % and 99 % were used. The measured variables were depth and pitch.

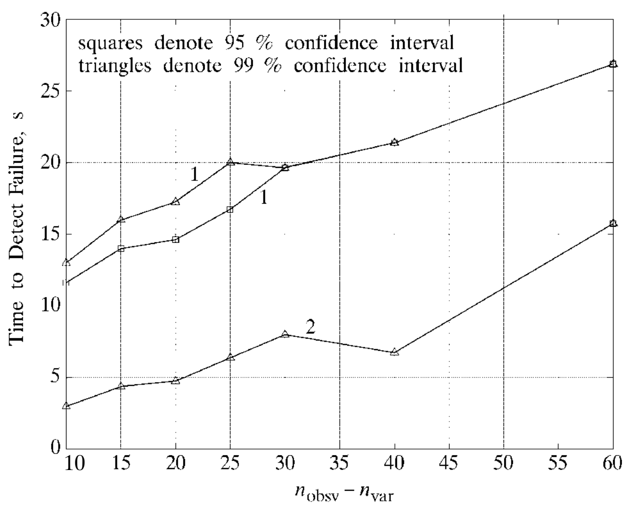

Fig. 4 Detection time for a stern plane jam occuring at 250 seconds

The figure indicates that, in the noise-free case, the detection time depends on the number of variables retained and the number of observations, but not strongly on the confidence interval. For fixed values of n_{var} and n_{obsv}, Figure 5 showed that $T^2_{Sum-\mathrm{threshold}}$ increases with decreasing α (larger confidence interval). In some cases, the T^2_{Sum} statistic computed for a block of data could be larger than the 95 % threshold but smaller than the 99 % threshold. This would lead to differences in the detection times.

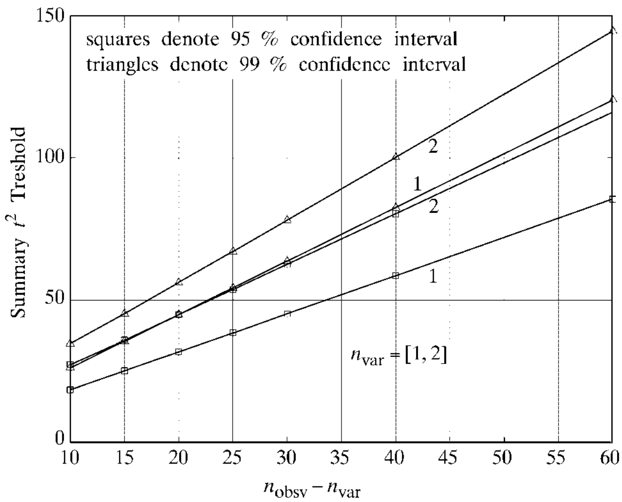

Fig. 5 T^2_{sum} statistic for 95 % and 99 % confidence intervals

This possibility is shown in Figure 4 for $n_{\mathrm{var}} = 1$ for the first four values of n_{obsv}. The difference in the detection times in each of these cases is one block length. For the larger values of n_{obsv}, the detection times are the same. Therefore, whenever the T^2_{Sum} statistic exceeded the 95 % threshold, it also exceeded the 99 % threshold.

With $n_{\mathrm{var}} = 2$, the detection times were independent of the confidence interval for the parameter values used here. It should also be noted that the detection times are shorter when 2 significant variables are retained than when only 1 variable is retained. This provides some justification for the retention of 2 variables in this work, even though that contradicts the discussion on the Parallel Analysis Method in Section II-C.

B.2 Rudder Jams

This set of simulations is virtually identical to the set just described. In each of these simulations, the rudder was jammed at its current value at a specified point in time. The time of the failure varied from 50 seconds to 600 seconds in 0.25 second increments, resulting in 2, 201 simulations. The number of significant variables that were retained after the PCA computations was 2, there were 17 sets of measurements in each block of data, and the threshold was computed for the 95 % confidence interval. As before, the measured variables for the vertical plane were depth and pitch, and for the horizontal plane they were roll and yaw.

Because of the similarity with the results just described, plots for the rudder jam detections are not presented. Correct classification of the fault as a rudder jam occurred in each of the 2, 201 simulations. There were no mis-classifications and no missed detections. The mean and maximum times of detection were 4.23 seconds and 15.9 seconds, respectively. The detection times are less than 8 seconds except in the interval of 322–350 seconds and for some of the simulations with failure times greater than 575 seconds. As another point of similarity with the stern plane jams just discussed, the rudder is reversing its direction of motion in the interval of 322–350 seconds.

It is clear that the T^2_{Sum} statistic for the horizontal plane motion exceeded its threshold in each of the 2, 201 simulations since correct classification occurred in all cases. However, it is also of interest to note that the T^2_{Sum} statistic for the vertical plane (stern plane jam detection) never exceeded its threshold in any of the simulations (at least not prior to or at the same time as the rudder jam detection).

The same analysis of the effects of n_{var}, n_{obsv}, and α on the detection times that was done for stern plane jams was repeated for rudder jams, with very similar results. It should be noted that much faster detection times are achieved with $n_{\text{var}}=2$ than with $n_{\text{var}}=1$.

C. Simulations Involving Measurement Noise

The only differences between the basis and the »real« simulations described in the previous sections were due to a stern plane jam or a rudder jam. Up to the time that the jam occurred, the simulation with the jam was identical to the basis simulation. Therefore, there was essentially no chance of false alarms or premature detections of fault conditions. With the presence of measurement noise, the probability of false alarms, premature detections, and mis-classifications increases. Longer detection times may be necessary if the data block length is increased to provide some filtering action.

In order to test the detection/classification algorithm under more realistic conditions, a number of simulations were run adding noise to the depth measurement. The MATLAB random number generator was used to produce a uniformly distributed value in the range -0.224 to $+0.224$ feet at each sample time. This value was added to the depth value computed by SIMULINK. The noise-corrupted value was used as an input to the controller, and thus was able to influence other variables as well.

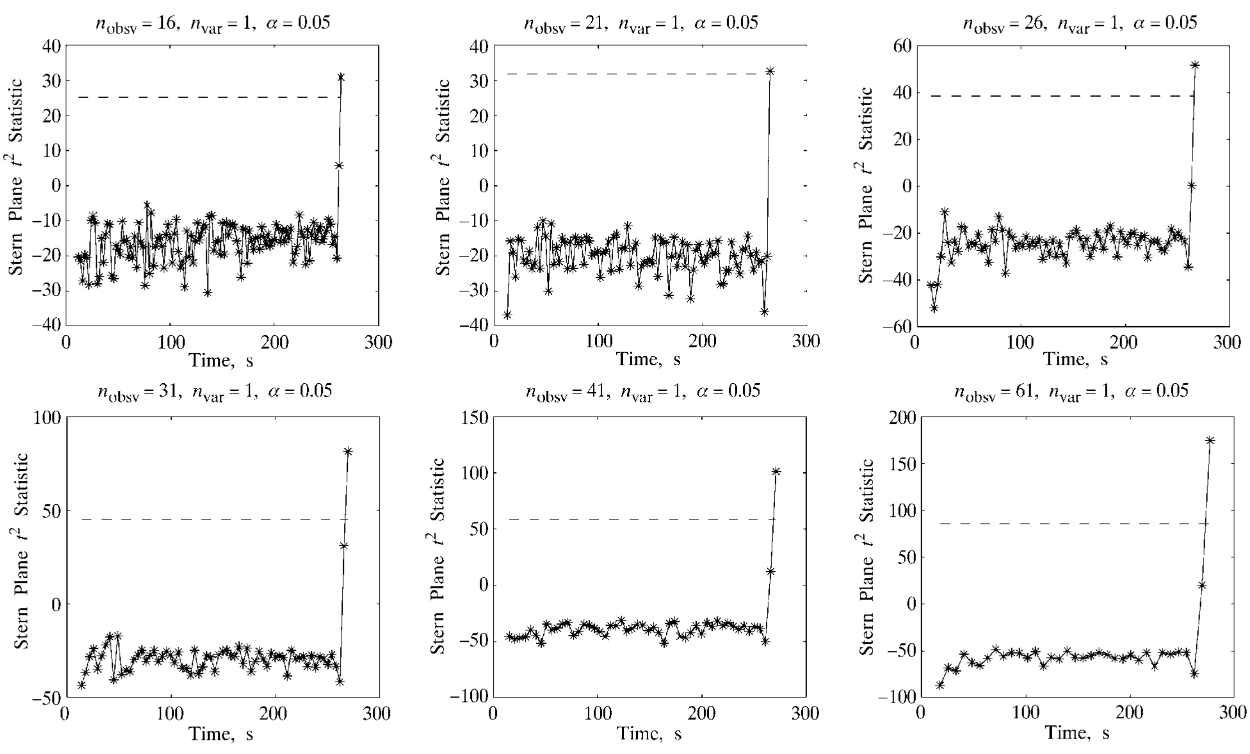

Fig. 6 Stern plane jam detection with noisy depth measurement

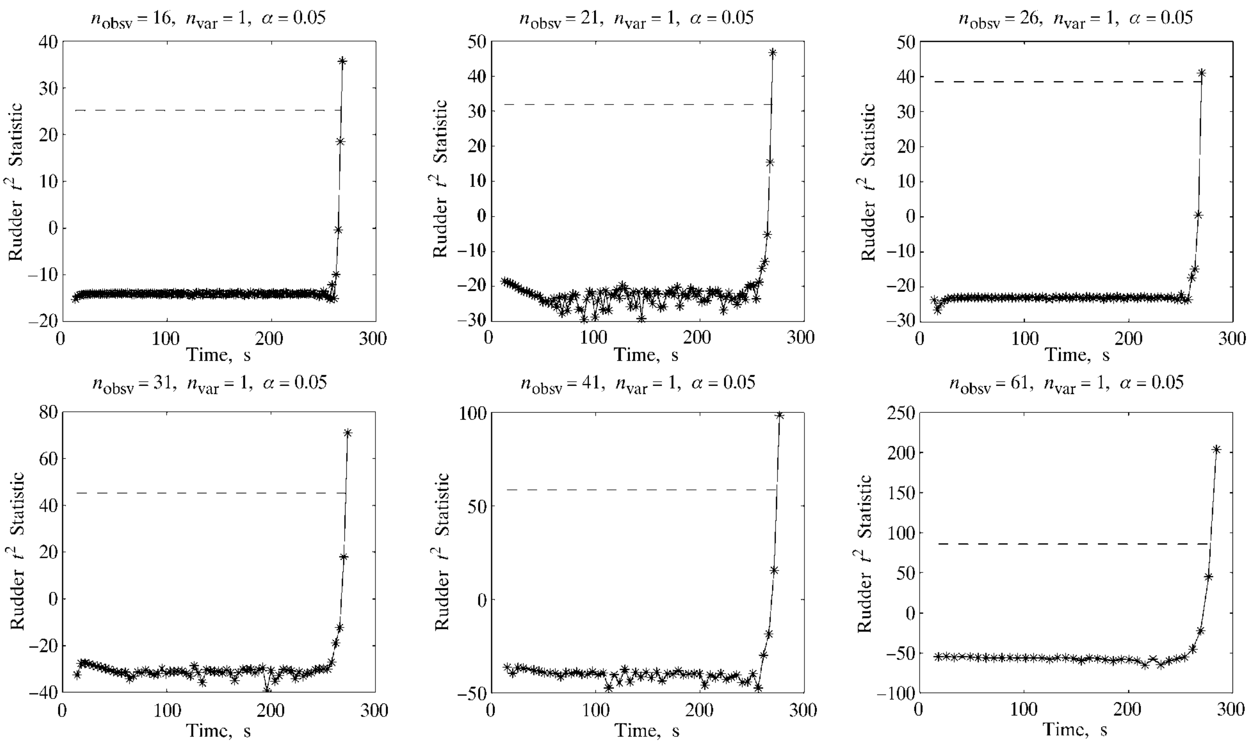

Fig. 7 Rudder jam detection with noisy depth measurement

The simulations that will be described in this paper consist of either a stern plane jam occurring at 250 seconds, a rudder jam occurring at 250 seconds, or no jamming at all. All the simulations were performed at 12 knots. The simulation data were processed by the fault detection algorithm, and the results were analyzed to evaluate the algorithm's performance. The number of variables, number of observations, and confidence interval were varied during the evaluation to determine the effects of those parameters.

Figures 6 and 7 illustrate some of these results. These figures show the T^2_{Sum} statistic plotted up to the time the threshold is exceeded. Figure 6 is the stern planeT^2_{Sum} statistic for the simulations with stern plane jams, and Figure 7 is the rudder T^2_{Sum} statistic for the simulations with rudder jams. The plots indicate that detection and correct classification are still possible when measurement noise is present. However, the detections times are longer than in the noise-free case.

In addition to the longer detection times, two other problems were observed with the noisy simulations. When the detection/classification algorithm was tested with $n_{var} = 2$, premature detection resulted in each simulation, and mis-classification resulted in the simulations of stern plane jams. Thus, whenever $n_{var} = 2$ was used, the classification was for a rudder jam, and the time of detection was prior to the time of failure. Apparently, the additional variable with a small singular value truly is acting like a noise source, as mentioned in Section II-C.

The other major problem was the occurrence of false alarms. In each of the simulations with no failure, a fault was detected and classified as a rudder jam. It is clear that additional research is needed to make the detection algorithm robust to measurement noise. The accuracy of the noise models must also be checked.

4 CONCLUSIONS

The results that we have obtained so far in the task of failure detection and classification are very promising. They indicate that the T^2 statistic, coupled with the use of PCA and the summary T^2_{Sum} statistic, is a reliable method to detect changes in the system that would require controller reconfiguration. In the evaluations of this method that have been performed to date, it has produced rapid and reliable detection and classification of major faults when measurement noise was not present. Reliable detection and classification of these faults have also been demonstrated in certain situations when measurement noise was included in the simulations.

If the fault that is detected is a major fault, such as a stern plane jam, then the controller reconfiguration is the implementation of a set of emergency recovery procedures, rather than just a change in controller parameters. These procedures can be predefined and implemented as necessary. If the fault is less severe, then good performance of the system can be maintained by changing parameters in the controller. Based on previous work done for our sponsor, it appears that the Linear Quadratic Gaussian (LQG) method will provide an approach to on-line control design.

Based on the work that we have done, it is clearly advantageous to generate the basis data on-line. This allows the model to receive the same reference inputs as the actual system. Thus, there are no problems with trying to store precomputed basis data for all possible scenarios or trying to scale or combine basis data computed for certain typical maneuvers. The recursive neural network (RNN) developed by the sponsor should be ideal for this purpose.

Work is continuing on this approach to fault detection and classification. A major task is to determine accurate sensor models and measurement noise models in order to obtain more realistic simulations. The detection/classification algorithm will be evaluated with these models included and modified as necessary to reduce noise sensitivity. Additional scenarios for changes to submarine parameters, such as loss of the speed sensor, will also be tested.

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Detekcija i klasifikacija kvarova na bespilotnoj ronilici uporabom T^2 statistike. Detekcija i klasifikacija kvarova kritični su koraci kod primjene upravljanja s promjenjivom strukturom. Članak opisuje Hottelig T^2 statistiku koja je primijenjena na detekciju i klasifikaciju zaglavljenja krmenih zakrilaca i kormila kod bespilotnih ronilica. Prikazani su simulacijski rezultati sa i bez šuma mjerenja. Rezultati pokazuju da je predloženi postupak sposoban brzo i pouzdano detektirati i klasificirati ove kvarove.

Ključne riječi: detekcija kvara, klasifikacija kvara, upravljanje s promjenjivom strukturom

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